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14. ABSTRACT
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pattern recognition, correlation, synthetic discriminant function (SDF), and Radon transform

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Power-Law Radon-Transformed Superimposed Inverse Filter Synthetic Discriminant Correlator for Facial Recognition

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ABSTRACT

A power-law correlation based on an inverse filter Fourier-Radon-transform synthetic discriminant function (SDF) for facial recognition is proposed. In order to avoid spectral overlap and nonlinear crosstalk, superposition of rotationally variant sets of inverse filter Fourier-transformed Radon-processed templates is used to generate the SDF. For the inverse filter, the Fourier transform of M projections (Radon Transform) from one training image is combined with (N-1) M Fourier transform of M projections taken from another N-1 training image. This synthetic SDF filter has a very high discrimination capability; however, it is not noise robust. To overcome this problem, a power-law dynamic range compression is added to the correlation process. The proposed filter has three advantages: (1) high discrimination capability as an inverse filter, (2) noise robustness due to dynamic range compression, and (3) crosstalk-free nonlinear processing. The filter performance was evaluated by established metrics, such as peak-to-correlation energy (PCE), Horner efficiency, and correlation-peak intensity. The results showed significant improvement as the power-law filter compression increased.

Keywords: pattern recognition, correlation, synthetic discriminant function (SDF), and Radon transform

1. INTRODUCTION

Facial recognition using optical correlators, combined with training techniques such as synthetic discriminant functions (SDFs) is associated with some limitations in algorithms for correlation-based distortion-invariant recognition systems. One of these limitations is more evident when the matched filter[1] is used. Matched filter is the optimal filter that provides the maximum signal-to-noise ratio for white Gaussian noise sample distribution for the recognition of undistorted images. The SDF, introduced by Caulfield and Malony[2] and by Hester and Casasent,[3] are the primary efforts in dealing with the problem of distortion-invariant recognition systems. There are numbers of significant advances made in relation to the SDF such as the minimum average correlation energy[4] and the minimum variance SDF filters.[5] There have been also the phase-only and the binary phase-only implementations[6,7] that made important practical advances in the recognition of distorted images. One of the problems with the SDF is the use of the entire two-dimensional (2-D) image in designing the filter, which leads to a filter response containing a composite image at any given point in space. This results in many cross correlation terms not matching any of the input images.[8] Therefore Riasati and Abushagur[9] proposed a new matched filter SDF design based on the projection-slice theorem (PST). In this design, the images are generated via a few slice projections of the object enabling a sparse collection of the information data. The collection of these cross-sections is sufficient for re-creating the object's real image. The 2-D projection-slice theorem is defined as follows: the Fourier transform of the projection of a two-dimensional function onto a line is equal to a slice through the origin of the two-dimensional Fourier transform of that function which is parallel to the projection line. The mathematical expression for PST is a two dimensional Radon transform. The inverse Radon transform is used to reconstruct medical images from computed tomography scans[10].

Alsamman and Alam[11], used a linear superposition of several image Fourier transform projections of images selected from training templates as the synthetic matched template within fringe adjusted correlator. As stated above, the Matched filter is the optimal filter for detecting signals embedded in zero-mean Gaussian noise and the SDF design is appropriate for detecting targets within a noisy clutter; however, in facial recognition, noise is not significant, unless the picture is taken in dark. Therefore for facial recognition purposes, it is better to use a high discriminant correlation filter. For instance, an inverse filter is known as a high discriminative correlation filter; however, this filter can be a poor choice for improving the signal-to-noise ratio.

In order to avoid spectral overlap and nonlinear crosstalk, and also in order to have a high discriminative correlation filter with the capability of improving the signal-to-noise ratio, we propose the superposition of rotationally variant sets of Fourier-transformed Radon-processed templates to generate the synthetic discriminant function (SDF) with the use of a power-law correlation based inverse filter.

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The proposed filter has the following advantages: (1) high discrimination capability as an inverse filter, (2) noise robustness due to power-law dynamic range compression, and (3) crosstalk-free nonlinear processing.
The filter performance was evaluated by established metrics, such as peak-to-correlation energy (PCE)[8,12], Horner efficiency[13], and correlation peak intensity. The results show significant improvement as the power-law compression increases.

2. RADON TRANSFROM INVERSE SDF FILTER

The composite image created by the SDF algorithm from several training images, is generated via weighted average of the various frequency components of the training images.
According to the projection-slice theorem (PST), the Fourier transform of the projection of a two-dimensional function onto a line is equal to a slice through the origin of the two-dimensional Fourier transform of that function which is parallel to the projection line[10]. This is defined as a two dimensional Radon transform which is the mathematical expression for PST. A composite image can be generated of different slices from training images so that the frequency components from different images do not overlap.
The final composite slice projection matched filter SDF is defined as:

$$P_M(u,v) = \sum_{n=1}^{N-1}\sum_{m=0}^{M-1} a_n T_n(\omega\cos\phi_{mn}, \omega\sin\phi_{mn}) \tag{1}$$

While the composite slice projection inverse filter can be defined as:

$$P_I(u,v) = \sum_{n=1}^{N-1} \frac{a_n}{\sum_{m=0}^{M-1} T_n(\omega\cos\phi_{mn}, \omega\sin\phi_{mn})} \tag{2}$$

where N is the number of training images, M is the number of slices taken from each image, T_n is the n'th training image, a_n is the SDF coefficient corresponding to the n'th training image, and u and v are the frequency variables for the Cartesian coordinate, while ω and Φ are the frequency variables in the polar coordinate systems:

$$u = \omega\cos\phi \tag{3}$$

$$v = \omega\sin\phi \tag{4}$$

And Φ_{mn} is determined by:

$$\phi_{mn} = \frac{m\pi}{M} + \frac{n\pi}{MN} \quad for \quad n = 1,....N-1, \quad m = 0,1,.....,M-1$$

The correlation results for the matched and inverse composite filters respectively are:

$$FFT\left[S(\mu,\nu)P_M(\mu,\nu)\right] \quad (5) \quad \text{and} \quad FFT\left[S(\mu,\nu)P_I(\mu,\nu)\right] \quad (6)$$

where $S(u,v)$ is the input image.
In facial recognition, the input images are not usually noisy. Therefore, it is better to use the inverse filter version of the SDF for better discrimination. However, for the pictures taken in dark conditions, the images can be noisy. Therefore, an improved version of the inverse filter is required.

One way to reduce noise is to introduce dynamic range compression on the Fourier spectrum of a noisy image. Dynamic Range Compression/Expansion known as companding (compressing-expanding) is a well-established principle for recovering the signal embedded in high noise. When dynamic range compression nonlinearity is applied to a noisy signal, it improves the signal to noise ratio in areas where the signal is low relative to noise and reduces the SNR in areas where the signal is higher than the noise level.

In Fourier processing, applying dynamic range compression not only enhances the signal to noise ratio where the signal is lower than the noise, it also has two additional effects: (a) increases noise frequency, and (b) enhances the high frequencies compared to the low frequencies. Increasing noise frequency leads to spreading noise over larger areas in the spatial domain. These three effects lead to a significant signal to noise ratio improvement within the processed data. We have already demonstrated the performance of dynamic range compression in both optical correlation[14-17] and compression deconvolution[18-20].

In this paper we use power-law dynamic range compression in the Fourier plane. Accordingly the correlation results can be rewritten as:

$$FFT\left[S(\mu,\nu)P_I(\mu,\nu)\right]^n \tag{7}$$

where n is less than 1 for compression purposes.

3. COMPUTER SIMULATION

Figure 1 shows the templates used in constructing the SDF filter. These images have been selected from the Georgia Tech face database[21]. We focused on the faces' regions of interest (ROI) consisting of the eyes, the nose, and the eyebrows which are the most important features in facial recognition. Each template (faces' ROI) was 89 x 102 pixels and was inserted in the center of a 256 x 256 pixels zeros array.

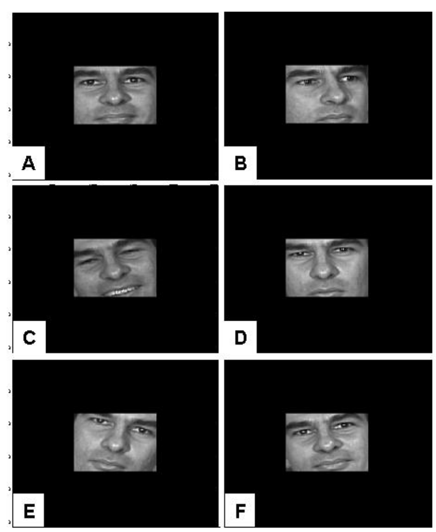

Figure 1. The templates used in constructing the SDF

For constructing the SDF filter, 18 slice-projections were selected from each image. The respective angle between the images' projections was one degree. Figure 2 shows the corresponding constructed Radon-processed (slice- projected) images from the templates shown in Figure 1.

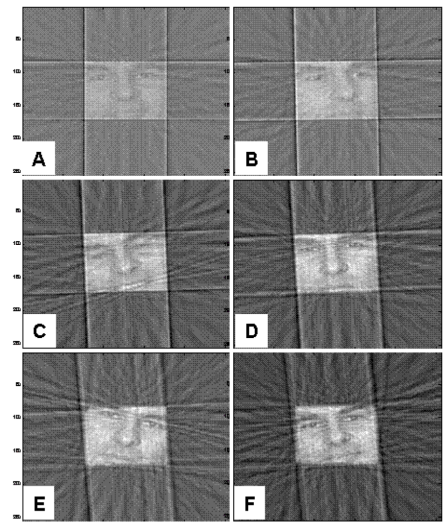

Figure 2. Constructed images from 18 slice projections with one degree rotation

Figure 3(A) shows the impulse response of the matched filter SDF which consists of the linear superposition of the Fourier transform of the Radon processed images shown in Figure 2 and Figure 3(B) shows the impulse response of inverse filter SDF which consists of linear superposition of the inverse of the Fourier transform of the Radon processed images shown in Figure 2.

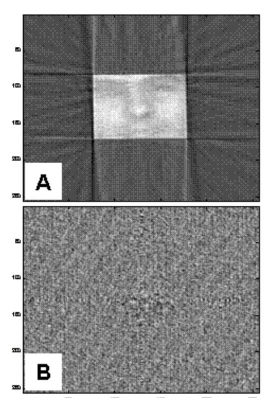

Figure 3. (A) Matched filter sliced projection SDF impulse response (B) Inverse filter sliced projection SDF

The discrimination capability of matched filter sliced projection SDF and inverse filter sliced projection SDF are demonstrated in Figure 4. This figure shows the correlation results of these two filters for in-class and out-of-class cases. For the in-class case, a broad correlation peak has been observed when we used the matched filter SDF, while a narrow correlation peak was observed when the inverse filter SDF was used. For the out-of-class case, the matched filter SDF showed a significant correlation peak, while the correlation peak completely disappeared when the inverse filter SDF was used. This shows the high discrimination capability of an inverse filter.

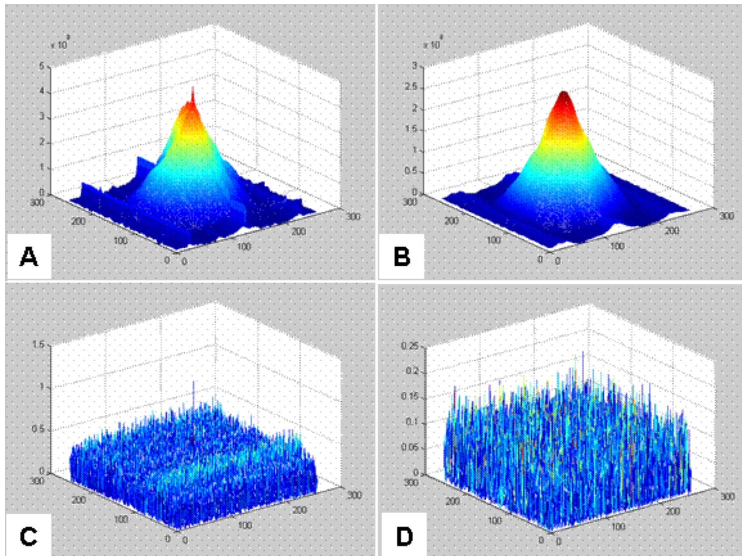

Figure 4. Correlation results for (A) in-class case with matched slice projection SDF, (B) out-of-class case with matched slice projection SDF, (C) and (D) in-class and out-of-class cases with an inverse slice projection SDF respectively.

In facial recognition with low illumination condition (dark environment), the noise can become a significant factor in recognizing the image. In order to simulate the noise effect of the correlation performance, a zero mean Gaussian noise was added to the images. In our simulation, the signal-to-noise ratio was 10.

Figure 5 (A, B, C, and D) show the correlation results with the power-law dynamic range compression for n=1, 0.7, 0.5, 0.1 respectively. For n=1, the correlation peak disappears completely within the noise. However, by increasing the severity of the dynamic range compression, the correlation peak enhances relative to surrounding noise.

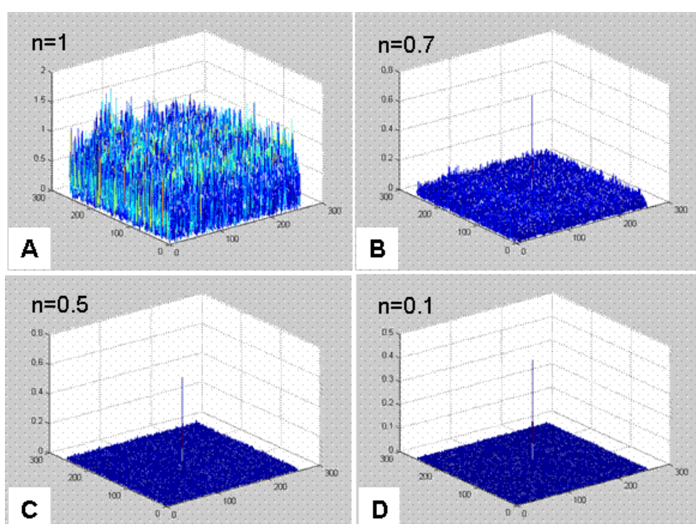

Figure 5. A, B, C and D are correlation results using the inverse sliced projection SDF with the power-law dynamic range compression for n=1, 0.7, 0.5 and 0.1 respectively.

The full effect of the dynamic range compression on the correlation peak enhancement was evaluated using three metrics, the correlation peak-intensity I_p, the peak-to-correlation energy (PCE) and the Horner efficiency. The results for these metrics are presented respectively in Figures 6A, 6B and 6C. As it is evident from Figure 6A, the best correlation peak intensity is achieved when there is no dynamic range compression (high values of n). The correlation peak intensity increases nearly by a factor of 4, as the power-law dynamic range compression approaches 1 (no dynamic range compression).

The degradation in the correlation peak intensity as the dynamic range compression increases is attributed to the fact, that most of the correlation spectrum with inverse filter SDF for certain projections is equal to one, which makes all the spectrum energy to be fully contributed to the correlation energy in the form of delta functions. On the other hand, when dynamic range compression is applied to the Fourier spectrum, the Fourier spectrum whitens near the value of 1; however, it contains three components: (1) the nonlinear interference between the correlation spectrum and noise spectrum, (2) the correlation spectrum, and (3) noise spectrum. This means that the correlation peak is less since these components affect the portion of the spectral energy to which the correlation energy intensity belongs. This explains the degradation in the correlation peak as the power-law dynamic range compression increases.

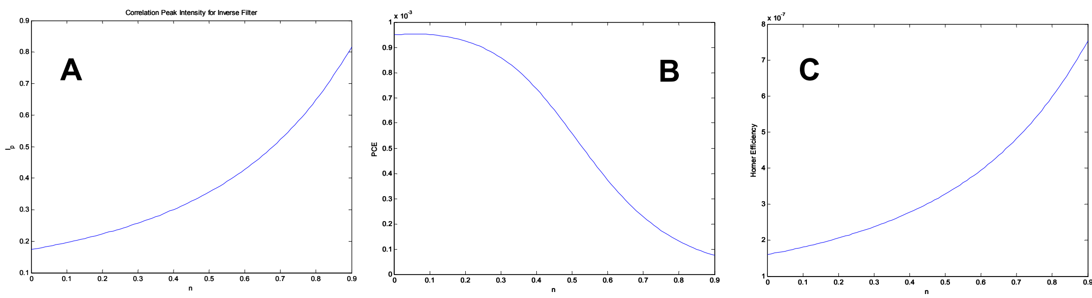

Figure 6. Plots of the correlation results (A) Correlation peak intensity, (B) peak to correlation energy, and (C) the Horner efficiency

Unlike the correlation peak intensity behavior, the PCE improves as the dynamic range compression increases. This could be attributed to two reasons: (1) the dynamic range compression offsets the signal-to-noise ratio degradation in particular at high frequency components due to the inverse filtering process, and (2) the dynamic range compression increases the noise frequency leading to spreading the noise over a very large area in the spatial plane. The PCE has been improved by nearly a factor of 9 as the power-law decreases from a value of 0.9 to 0.1.

4. CONCLUSION

In this paper, we have presented a power-law inverse filter projection-slice (Radon Processed) SDF for a noise robust, highly discriminative correlator for facial recognition. The performance of this system has been evaluated by several metrics including correlation peak intensity, peak-to-correlation energy and Horner efficiency. The computer simulation results showed the effectiveness of this approach in discriminating and detecting images embedded in noise.

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